Development of Noise Suppression Schemes in Images

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Thesis submitted in

May 2013

to the department of

Computer Science and Engineering

of

National Institute of Technology Rourkela

in partial fulfillment of the requirements

for the degree of

Master of Technology

by

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June 2, 2013

Certificate

This is to certify that the work in the thesis entitled ***Development of Noise Suppression Schemes in Images*** by ***Sarmila Padhy*** is a record of an original research work carried out by her under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of *Master of Technology* in *Computer Science* in the department of Computer Science and Engineering, National Institute of Technology Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Ratnakar Dash

Acknowledgement

I owe my deepest gratitude to the ones who have contributed greatly in completion of this thesis.

Foremost, I would like to express my sincere gratitude to my supervisor, *Prof. Ratnakar Dash*, who has provided me with continuous encouragement, guidance and support from initial to final level to carry out this research. His dedication and consistent notation in my writings has motivated me to work for excellence.

I am very much indebted to *Prof. Ashok Kumar Turuk*, Head-CSE, for his continuous encouragement and support. I am also thankful to all the professors, co-researchers, batch mates and friends at National Institute of Technology Rourkela for their active or hidden cooperation. Their contribution can never be penned with words. I must acknowledge the academic resources that I have got from NIT Rourkela. I would like to thank administrative and technical staff members of the Department for their cooperation.

Finally, my heartfelt thanks to my husband *Prabhat* for his unconditional love and support. Words fail me to express my gratitude to my beloved parents who sacrificed their comfort for my betterment.

Sarmila Padhy

Abstract

Noise suppression from images is one of the most important concerns in digital image processing. Two important noise models are considered in this thesis i.e. random valued impulse noise and Gaussian noise and two propositions have been made to suppress these noises. One of the proposed scheme deals with random valued impulse noise model whereas, the other one deals with Gaussian noise. The first scheme is detection based filtering which uses the Bayes' classification technique to detect the noisy pixels. The detected noisy pixels are then filtered out using a weighted median filtering while keeping other pixel values unchanged. In another scheme an attempt has been made to improve the existing spatially adaptive denoising algorithm for suppression of Gaussian noise. The proposed scheme uses uniform weighting coefficients and utilizes local statistics parameters to detect as well as to filter the noisy pixels. The suggested scheme gives good results for images corrupted with high level Gaussian noise (i.e. less than 10dB).

Extensive simulations on standard images are carried out to show the efficiency of the proposed schemes along with other state of the art techniques under similar environment. Subjective as well as objective performance comparisons show the better noise suppression capability of the proposed algorithms than their counterparts.

***Keywords*:** Image restoration, Random valued impulsive noise, Gaussian noise, Bayesian classifier, Local statistics parameters.

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Chapter 1

Introduction

Chapter 1

Introduction

Vision is a process which requires number of components of the human eye and brain to work together. The sense of vision is one of the most important senses for human survival and evolution. Visual system is used by humans to see or acquire visual information. The field of image processing emphasizes on automating the process of gathering and processing visual information. Like visual sensory system of humans, *digital image processing* involves the process of acquiring, manipulating, and analyzing visual information by digital computer [1]. Usually, a digital image is represented as a two dimensional array of finite size comprising of real or complex numbers by a finite number of bits, and mathematically represented as,

$$I = f(x, y) \tag{1.1}$$

where $f(x, y)$ is a pixel at location (x, y). Amplitude of f at any pair of coordinates is proportional to the brightness of the image at that point. This is usually known as intensity or gray level. When spatial coordinates and amplitude values are all finite, discrete quantities, then the image is called digital image. Digital image processing has many advantages in terms of cost, speed and flexibility etc. It has become the dominant method in use due to increasing performance of personal computers. Digital image processing is used in almost every discipline of science & engineering including medical, entertainment, industry, military and civil etc. In each of the applications, the objective is to extract information about the scene being imaged [2]. Digital image processing may be categorized into various subbranches based on methods whose:

(i) Input and output are images.

(ii) Inputs may be images whereas, outputs are attributes extracted from those images.

Different image processing functions based on the above two classes are listed below.

(i) Image restoration

(ii) Color image processing

(iii) Multi resolution processing

(iv) Compression

(v) Morphological processing

(vi) Segmentation

(vii) Representation and description

(viii) Object recognition

The inputs and outputs are images for the first seven functions, whereas for the rest three the outputs are attributes from the input images [3]. The actual solution of a specific problem requires a significant research and development. The entire process of image processing, may be divided into three major stages which are given below:

(i) Discretization and representation: Process of converting visual information into a discrete form, suitable for computer processing and approximating visual information to save storage space as well as time requirement in subsequent processing.

(ii) Processing: Process of improving image quality by filtering and compressing data to save storage during transmission.

(iii) Analysis: Process of extracting image features, quantifying shapes, registration and recognition.

In the first stage, visual information is the input and its corresponding digital image is the output. In the second stage, both the input and the output are images but, the output is an improved version of the input. In the final stage, the input is still an image but the output is a description of the contents of that image [4]. Enhancing the image quality without loss of features of the image is the main task of noise suppression. Noise suppression is the one of the preprocessing stage of the image processing. Out of the sub branches of digital image processing, this thesis deals with image restoration. To be precise, this thesis devotes on a part of the image restoration i.e. suppression of noise from images. Accurately, it is about the suppression of two particular types of noise i.e. random valued impulsive noise and Gaussian noise.

1.1 Image Restoration

The process of recovering an image from a degraded observation by using apriori knowledge of the degradation phenomenon [5] is known as image restoration. Three kinds of degradation are there in image processing.

(i) Degradation due to blur

(ii) Degradation due to noise

(iii) Degradation due to both blur and noise

In this thesis, an effort has been made on removing the noise from degraded images. The degraded image $g\left(x,y\right)$ is represented as,

$$g\left(x,y\right)=f\left(x,y\right)+\eta\left(x,y\right) \tag{1.2}$$

where $f\left(x,y\right)$ is the true image and $\eta\left(x,y\right)$ is the additive noise.

Knowing the amount of noise is very important to allow algorithms to adaptively filter images instead of using fixed thresholds. Generally the exact value of the noise variance is required which is a crucial filter parameter. However, estimation of accurate noise variance is difficult due to the intermixing of statistics of the original image and the noise. The separation of the two signals is not an easy task and it is well known that the noise variance of the sum of two independent signals is the sum of the variances of the two components [6].

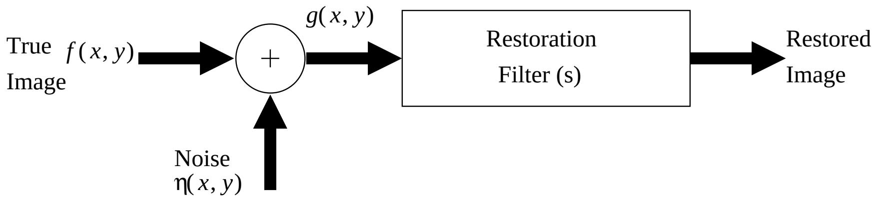


Figure 1.1: Model of the noise removal process.

1.2 Noise Models

Image noise is generally an unwanted, variation in brightness or color information in an image. It is also random in nature. It can obtained in film grain, or in the input device (scanner or digital camera) sensor and circuitry, or in the ideal photon detector. It is introduced into images at the time of acquisition and transmission of images. It is most apparent in image regions such as shadow regions or underexposed images which are associated with low signal level. High levels of noise are not desirable always, but there are cases when lower levels of noise may be required, for example to prevent discretization artifacts. Noise purposely added for such purposes is called dither [7]. Different types of noise models are described below.

Impulsive noise:

Impulsive noise is introduced to the images during transmitting image data over an unsecured communication channel, while it can also be introduced by acquiring. It is defined as changing a part of the pixel values with random ones. Impulsive noise removal algorithms are rank ordered statistic filters, which depend on the pixel values of the neighborhood to correct the noisy pixel. Noise suppression is essential to obtain workable images. Impulsive noise can be divided as *salt-and-pepper noise (SPN) and random valued impulse noise (RVIN)*. An image having impulsive noise can be described as follows:

$$x\left(i,j\right)=\begin{cases}\eta\left(i,j\right)\text{with probability (p)}\\ y\left(i,j\right)\text{with probability (1-p)}\end{cases} \tag{1.3}$$

where $x\left(i,j\right)$ denotes a noisy image pixel, $y\left(i,j\right)$ denotes a noise free image pixel and $\eta\left(i,j\right)$ denotes a noisy impulse at the pixel location $\left(i,j\right)$.

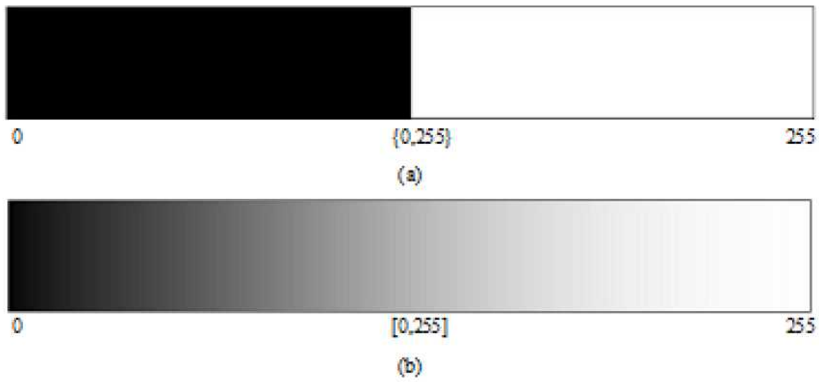


Figure 1.2: (a) Representation of salt-and-pepper noise with $\eta\,(i,j)\,\epsilon\{L_{min}, L_{max}\}$, (b) Representation of random valued impulse noise with $\eta\,(i,j)\,\epsilon[L_{min}, L_{max}]$.

In salt-and-pepper noise, noisy pixels take either minimal or maximal values i.e. $\eta\,(i,j)\,\epsilon\{L_{min}, L_{max}\}$ but for random valued impulse noise, noisy pixels take any random value within the range minimal to maximal value i.e. $\eta\,(i,j)\,\epsilon[L_{min}, L_{max}]$ where, L_{min} and L_{max} denote the lowest and the highest pixel luminance values within the dynamic range respectively. Pixels related with random valued impulse noise and their surroundings exhibit very similar behavior. These pixels differ less in intensity [8].

Shot noise:

The noise in the lighter parts of an image from an image sensor is caused by statistical quantum fluctuations, which is, variation in the number of photons sensed at a given exposure level is known as photon shot noise. This type of noise has a root-mean-square value which is proportional to the square root of the image intensity. In this type, noises at different pixels are independent of one another. Shot noise is having poisson distribution, which is generally not very different from Gaussian. In addition to this photon shot noise, there can be also another shot noise from the dark leakage current in the image sensor. This type of noise is known as dark shot noise or dark current shot noise.

Speckle noise:

Speckle noise is multiplicative in nature. This type of noise is introduced in laser, acoustics and synthetic aperture radar coherent imaging systems. The source

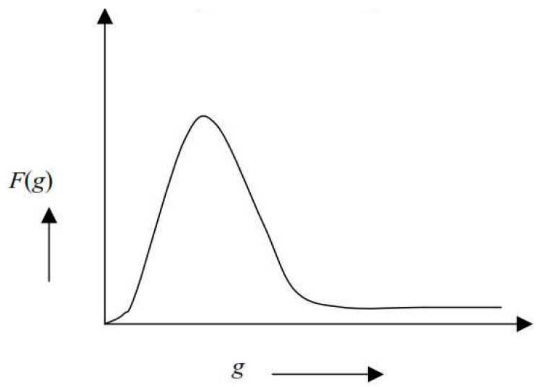


Figure 1.3: Gamma distribution

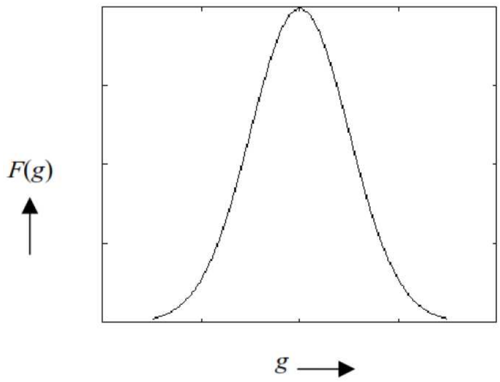


Figure 1.4: Gaussian distribution

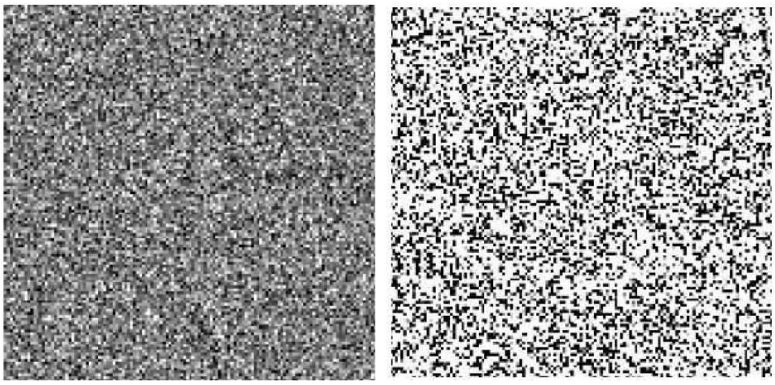
of this noise is attributed to random interference between the coherent returns. Speckle noise is having gamma distribution which is represented as,

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{\frac{-g}{a}} \tag{1.4}$$

where $a^2\alpha$ is variance and g is the gray level. The gamma distribution is shown in Figure 1.3.

Amplifier noise (Gaussian noise):

The standard model of Gaussian noise is additive, independent at each pixel and independent of the signal intensity [9]. Generally, when an original image is degraded by additive white Gaussian noise which is signal independent, then the usual degradation model at a point can be represented in (1.2). This type of noise is characterized by adding to each image pixel, a value from a zero mean Gaussian distribution. Such noise is generally added during image acquisition.



(a) (b)

Figure 1.5: (a) Gaussian noise (mean=0, variance=0.05) and (b) Gaussian noise (mean=1.5, variance=10)

The zero mean property allows the Gaussian noise to be removed by locally averaging pixel values. Removing Gaussian noise would involve smoothing inside the distinct regions of an image without degrading the sharpness of their edges. Gaussian noise removal algorithms ideally should be as accurate as possible to detect edges in the image. This type of noise has a Gaussian distribution [10], which has a bell shaped probability distribution function given by

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} \tag{1.5}$$

where g represents the gray level, m represents the mean or average of the function, and σ represents the standard deviation of the noise. Its distribution is shown in Figure 1.4.

Brownian noise:

Brownian noise belongs to the fractal or $\frac{1}{f}$ noises. The mathematical model for $\frac{1}{f}$ noise is fractional Brownian motion which is a non stationary stochastic process that follows a normal distribution. Brownian noise is a special case of $\frac{1}{f}$ noise. It is obtained by integrating white noise. It can be graphically represented as shown in Figure 1.6.

In this thesis two noise models are considered which can adequately represent most of the noise added to images: *additive Gaussian noise and impulsive noise.*

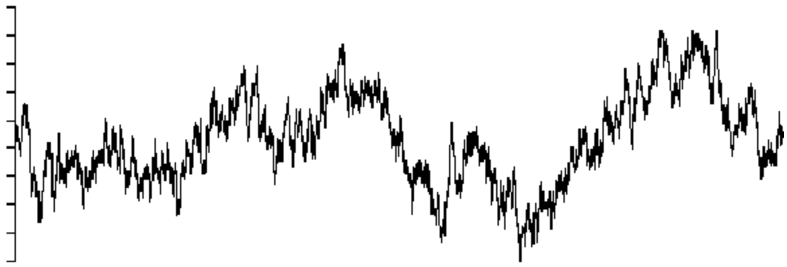


Figure 1.6: Brownian noise distribution

1.3 Filters

Generally, image denoising employs different types of filtering techniques. Filtering may be done either in the spatial domain or in the frequency domain [11]. Usually, filters may be classified into two categories

(i) Linear

(ii) Nonlinear

The filtering methodologies are described below.

Linear Filters:

Linear filters were the primary tools in the early development of image processing. Their mathematical simplicity and satisfactory performance in many applications made them easy to design and implement [12]. If noise is present, then the performance of linear filters is poor. They tend to blur edges, cannot remove impulsive noise effectively and cannot perform well in the presence of signal dependent noise. Mathematically, a filter may be defined as an operator $L(\cdot)$, which maps a signal x into a signal y:

$$y = L(x) \tag{1.6}$$

When the operator $L(\cdot)$ satisfies both the superposition and proportionality principles, the filter is said to be linear. The two dimensional and m-dimensional linear filtering are concerned with the extension of one dimensional filtering

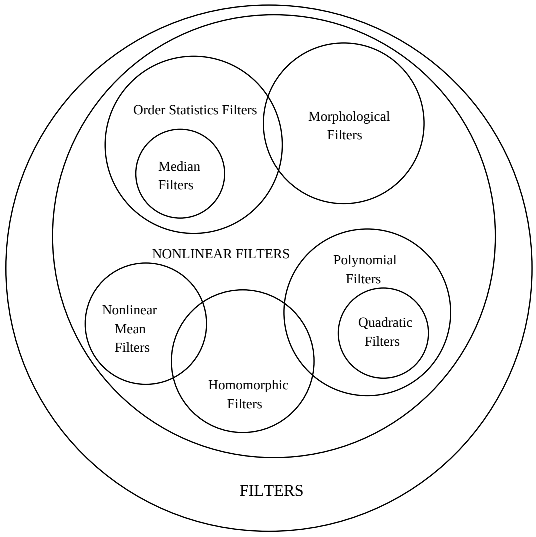


Figure 1.7: Nonlinear filter family

techniques to two and more dimensions. If the impulse response of a filter has only finite number of non zero values, then the filter is known as a finite impulse response (FIR) filter. Otherwise, it is known as an infinite impulse response (IIR) filter. The filter which evaluates the output image only with the input image, then the linear filter is known as non recursive [13]. Few main types of linear filters are given below:

Low-Pass Filter:This type of filter smooths the image and reduce high spatial frequency noise components.
High-Pass Filter:This type of filter enhances very low contrast features, when superimposed on a very dark or very light background.
Band-Pass Filter:This type of filter tends to sharpen the edges and enhance the small details of the image.

Nonlinear Filters: Nonlinear filters follow the same mathematical formulation as that of linear filter. However, in this case, the operator $L(\cdot)$ is not linear. Convolution of the input with its impulse response does not generate the output of a nonlinear filter. Gray scale transformations are the simplest nonlinear transformations. This corresponds to a memoryless nonlinearity which maps the signal x to y. The transformation

$$y = t(x) \tag{1.7}$$

may be used to transform one gray scale x to another y. Another form of intensity mapping is the histogram modification, where the relative frequency of gray level occurrence in the image is depicted. Order statistic filters for noise removal are the most popular class nonlinear filters. The median filter, the stack filter and the median hybrid filter etc. belong to this class of filters. Adaptive filtering has also taken advantage of nonlinear filtering techniques. Non adaptive nonlinear filters are usually optimized for a specific type of noise and signal. The nonlinear filter family is shown in Figure 1.7.

1.4 Performance Measures

The metric used for performance comparison of different filters are defined below.

Mean Squared Error (MSE) and Peak Signal to Noise Ratio ($PSNR$)
In statistics, the mean squared error or MSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. MSE is defined as,

$$MSE = \frac{1}{MN} \sum_{i}^{M} \sum_{j}^{N} (R_{i,j} - I_{i,j})^2 \tag{1.8}$$

where $R_{i,j}$ and $I_{i,j}$ represents the pixel values of the restored image and the original image respectively and $M \times N$ is the size of the image.

$PSNR$ uses a standard mathematical model to measure an objective difference between two images. It estimates the quality of a reconstructed image with respect to an original image. The basic idea is to compute a single number that reflects the quality of the reconstructed image. Reconstructed images with higher $PSNR$ values are judged better. The parameter peak signal-to-noise ratio ($PSNR$) is defined as,

$$PSNR(dB) = 10log10 \left(\frac{255^2}{MSE} \right) \tag{1.9}$$

1.5 Literature Review

The one of the emerging field of image processing is removal of noise from a contaminated image. Many researchers have suggested a large number of algorithms and compared their results. The main challenge is the removal of *impulsive and Gaussian noise* as well as preserving the image details. The number of noise suppression algorithms have been developed. Due to the low computational cost benefits mean filter, median filter and their modified approaches have been usually used. Impulsive noise removal consists of detecting the noisy pixel taking into account the edges and substituting the noisy pixel with the best approximation of the correct pixel value based on the neighborhood, whereas Gaussian noise removal consists of detecting the edges, preserve them for blurring and smoothing the locally smooth and distinct areas. Three types of filtering schemes are used for the noise suppression.

(i) Filtering without detection: In this type of filtering a window mask is moved across the observed image. The mask is usually of size $(2N+1)^2$, where N is a positive integer. Generally the center element is the pixel of interest. When the mask is moved starting from the left top corner of the image to the right bottom corner, it performs some arithmetical operations without discriminating any pixel.

(ii) Detection followed by filtering: This type of filtering involves two steps. In the first step it identifies noisy pixels and in the second step it filters those pixels. Here also a mask is moved across the image and some arithmetical operations is carried out to detect the noisy pixels. Then filtering operation is performed only on those pixels which are found to be noisy in the previous step, keeping the non noisy intact.

(iii) Hybrid filtering: In such filtering schemes, two or more filters are suggested to filter a corrupted location. The decision to apply a particular filter is based on the noise level at the test pixel location.

Simple adaptive median filter for the removal of impulse noise from highly corrupted images (SAWM)

In addition, Ibrahim *et al.* [14] has proposed a switching based adaptive weighted mean filter method, in which the pixels are roughly divided into two classes based on only the intensity values which are noise free pixel and noisy pixel. Adaptively changing the size of the median filter can be done based on the number of noise free pixels in the neighborhood.

Spatially adaptive denoising algorithm for a single image corrupted by Gaussian noise (SADA)

Nguyen *et al.* [15] has proposed one technique in which the parameters of local statistics are used for a single image corrupted by Gaussian noise. This method consists of two stages: noise detection and noise removal filtering. In noise detection stage, local statistics parameters are used to define the noise detection constraints. In filtering stage, a modified Gaussian noise removal filter based on the local statistics is defined for controlling the degree of noise suppression because this filter is an adequate way to handle the degree of local smoothness.

Adaptive center weighted median filter (ACWM)

Chen *et al.* [16] has proposed a novel adaptive algorithm, which forms estimates based on the differences between the current pixel and the outputs of center weighted median (CWM) filters with varied center weights. It employs the switching scheme based on the impulse detection mechanisms. It utilizes the center weighted median filter that have varied center weights to define a more general operator, which realizes the impulse detection by using the differences defined between the outputs of CWM filters and the current pixel of concern. The ultimate output is switched between the median and the current pixel itself.

Advanced impulse detection based on pixel wise MAD (PWMAD)

Crnojevic *et al.* [17] has proposed a robust estimator of variance, MAD (median of the absolute deviations from the median), used to efficiently separate noisy pixels from the image details. This algorithm is free of varying parameters, requires no previous training or optimization, and successfully removes all type of impulse noise. The median of the absolute deviations from the median is used to estimate the presence of image details, thus providing their efficient separation from noisy image pixels. An iterative pixel wise modification of MAD (PWMAD) provides reliable removal of arbitrarily distributed impulse noise.

Directional weighted median filter (DWM)

Another method is proposed by Dong *et al.* [18] for removal of random valued impulse noise is directional weighted median filter (DWM). This filter uses a new impulse detector, which is based on the differences between the current pixel and its neighbors aligned with four main directions. After impulse detection, it does not simply replace noisy pixels identified by outputs of median filter but continue to use the information of the four directions to weight the pixels in the window in order to preserve the details as removing noise. This method repeats 8 to 10 times. It gives the good performance when noise level is too high.

Block based noise estimation using adaptive Gaussian filtering

Shin *et al.* [19] has proposed a block-based noise estimation method, in which an image is filtered by an adaptive Gaussian filter which is corrupted by the additive white Gaussian noise. In this literature, Gaussian filter coefficients are selected as functions of the standard deviation of the Gaussian noise which is estimated from the difference of the selected block images between the noisy input image and its filtered image.

Fast method for noise level estimation and integrated noise reduction

Another method for noise level estimation and denoising is proposed by Bosco *et al.* [20] in which the standard deviation of additive white Gaussian noise in digital image is computed for the selected flat areas which is used to remove Gaussian noise. The problem of estimation of noise level is also addressed. This is an fast and efficient method to remove Gaussian noise from the images.

Fast and efficient algorithm to remove Gaussian noise in digital images

Vijayakumar *et al.* [21] has proposed a fast and efficient algorithm to remove Gaussian noise in digital images in which the amount of noise level is estimated in the first stage from the degraded image which is corrupted by additive white Gaussian noise. In the next stage, based on a threshold value the central pixel is substituted by the mean value of the surrounding pixels.

1.6 Motivation

Keeping the research directions in view, it has been realised that there exists enough scope to improve the restoration performance. In this thesis, an effort has been made to suppress noise from images. In particular, the objectives are narrowed to

(i) To work towards improved and efficient noise detectors for identifying contaminated pixels.

(ii) Devise algorithms to find the most complete and sound noise filter, so that noise suppression would be more reliable, is the primary motivation behind this work.

(iii) Adaptive choice for the parameters are investigated which are used to define the constraint of detection and to determine the coefficients of Gaussian filter. With this approach, it is expected that a more sophisticated formulation can be derived and better performance can be achieved.

(iv) To decrease the computational complexity of the algorithms.

1.7 Thesis Layout

Rest of the thesis is organized as follows —

Chapter 2: Suppression of RVIN Using Bayesian Classifier in an Image

In this chapter, one scheme is proposed to detect the noisy pixels. Using the

Bayesian classifier, noise detection is defined. A weighted median filter is used in the proposed method for effective noise suppression with preserving detailed information as compared to ACWM, PWMAD and DWM methods. Noise robustness of the proposed scheme is tested with different noise strengths.

Chapter 3: Improved Spatially Adaptive Denoising Algorithm to Suppress Gaussian Noise in an Image In this chapter, an improved Spatially Adaptive Denoising Algorithm (SADA) is proposed which leads to satisfactory results in terms of objective and subjective, when the image is corrupted with the SNR level less than 10dB of additive white Gaussian noise. In this proposed method, the parameters of local statistics are used for effective noise suppression with preserving detailed information as compared to PWMAD, SAWM and SADA methods. All the pixels including the diagonal elements of the local window with uniform weighting coefficients are taken in the proposed method for the noise detection and removal.

Chapter 4: Conclusion and Future Work This chapter provides the concluding remarks with more emphasis on achievements and limitations of the proposed schemes. The scopes for further research are outlined at the end.

The contributions made in each chapter are discussed in sequel, which includes proposed schemes, their simulation results, and the comparative analysis.

Chapter 2

Suppression of RVIN Using Bayesian Classifier

Chapter 2

Suppression of RVIN Using Bayesian Classifier

In impulse noise removal the main challenge is to suppress the noise as well as to preserve the details. Many filters with an impulse detector are proposed to remove impulse noise but in this method a new approach is suggested for removal of random valued impulsive noise from images which follows the detection followed by filtering scheme. The detection of noisy pixel is done using a Bayesian classifier method for the pixels in a test window and the filtering is done for the noisy pixels using a weighted median filter.

2.1 Bayesian classifier

Over the years, Bayesian classifier has evolved as one of the popular tools to be used in image processing. It is a framework for the formulation of statistical inference problems. It derives the posterior probability as a consequence of two antecedents, a prior probability and a likelihood function derived from a probability model for the data to be observed. The prior probability indicates one's preconceived beliefs about how likely different hypotheses are and also reflects our prior knowledge of how likely before the pattern actually appears. It is the collection of all possible values that the signal or the parameter vector can assume. The probability of observing given, is known as the likelihood. It indicates the compatibility of the evidence with the given hypothesis. The posterior signal or parameter space is the subspace of all the likely values of a signal or a parameter consistent with both the prior information and the evidence in the observation. It tells us the probability of a hypothesis given the observed evidence. It is determined by a combination of the inherent likeliness of a hypothesis (the prior) and the compatibility of the observed evidence with the hypothesis (the likelihood) [22]. The classification of a pattern vector using the Bayes classifier is done as follows.

Let x denote the n dimensional pattern vector and there be w_j , $j = 1, 2, ..., k$ classes. The probability of observing a random pattern vector x from the class w_j, using *Bayes rule* is defined as,

$$p(w_j|x) = p(x|w_j)\, p(w_j) \tag{2.1}$$

where $p(x|w_j)$ is the likelihood of w_j with respect to x, $p(w_j)$ is the prior probability and $p(w_j|x)$ is the posterior probability. Bayes formula shows that by observing the value of x, we can convert the prior probability $p(w_j)$ to the posterior probability $p(w_j|x)$. $p(w_j|x)$ means the probability of the state of nature being w_j given that feature value x has been measured. For Bayesian classification, posterior probability model for each class should be obtained. In binary classification, a signal x is labeled with the class that scores the *higher posterior probability*. In this chapter noise detection in the image is modeled as a pattern classification problem. Bayes classifier has been utilized to classify the pixels as noisy or non noisy. Details of the proposed scheme is provided in the following section.

2.2 Proposed Method

In Bayesian classifier, an image is a realization of a random matrix whose probability distribution is known apriori. There could be several ways to specify the prior probability distribution of a pixel in an image which is a discrete function defined over the set of pixel values, i.e., $\{0, 1, 2, ..., 253, 254, 255\}$. In the proposed method prior distributions are taken with the help of *assumptions and observations* of the corrupted image with RVIN. The proposed algorithm consists of two stages: *noise detection* and *noise suppression filtering*. The first stage consists of detection of noisy pixels and the next stage consists of suppression of the detected noisy pixels. To determine the noisyness of a pixel $x_{i,j}$, a window based approach is used. For this purpose, a window of size 3×3, is used and the center pixel is tested for its noise status. The intensity of the test pixel is used as the feature parameter to classify it into a particular category. The likelihood of the test pixel $x_{i,j}$ is considered as a Gaussian distribution, with two parameters mean and variance of the window. The mean is computed with the help of all the neighborhood pixels of the window which is defined as,

$$\mu_{i,j} = \frac{\sum_m \sum_n x\left(i+m, j+n\right)}{9} \tag{2.2}$$

Similarly, for the same test pixel $x_{i,j}$ variance is computed which is defined as,

$$\sigma_{i,j} = \frac{\sum_m \sum_n \left|x\left(i+m, j+n\right) - \mu_{i,j}\right|}{9} \tag{2.3}$$

The probabilities of the noisy pixels and noisy free pixels are chosen as apriori by *observing the noisy image.*
Now the likelihood of the pixel $x_{i,j}$ given noisy pixel is defined as,

$$p\left(I \mid noisypixel\right) = \frac{1}{\sqrt{2 \times \pi\sigma_{i,j}^2}} exp\left(\frac{-\left(I\left(x_{i,j}\right) - \mu_{i,j}\right)^2}{2\sigma_{i,j}^2}\right) \tag{2.4}$$

where I denotes the feature parameter which is the intensity of the observed pixel $x_{i,j}$. Then, the posterior probability of the pixel being noisy pixel is computed which is defined as,

$$p\left(x_{i,j}\right) = p\left(noisypixel\right) \times p\left(I \mid noisypixel\right) \tag{2.5}$$

where $p\left(noisypixel\right)$ is the prior probability of noisy and $p\left(I \mid noisypixel\right)$ is the likelihood of the pixel $x_{i,j}$ given noisy pixel. Similarly the likelihood of the pixel $x_{i,j}$ given noise free pixel is computed by using equation (2.4).
The posterior probability of the pixel $x_{i,j}$ being noise free pixel is computed which is defined as,

$$p1\left(x_{i,j}\right) = p\left(noisefreepixel\right) \times p\left(I \mid noisefreepixel\right) \tag{2.6}$$

where $p\left(noisefreepixel\right)$ is the prior probability of noise free and $p\left(I \mid noisefreepixel\right)$ is the likelihood of the pixel $x_{i,j}$ given noise free pixel.
Now the noise detection function is defined as,

$$flag\left(i,j\right) = \begin{cases} 1, & \text{if } p\left(x_{i,j}\right) > p1\left(x_{i,j}\right) \\ 0, & \text{otherwise} \end{cases} \tag{2.7}$$

If the $flag\left(i,j\right)$ value is equal to 1, then the pixel is detected as a noisy one. Means if the posterior probability of the pixel $x_{i,j}$ being noisy pixel is greater than the posterior probability of the pixel $x_{i,j}$ being noise free pixel, then that pixel belongs to the noisy pixel. This shows how the Bayes classifier affects the noise detection [23]. So, using the *Bayesian classifier*, noise detection is defined and the pixels of the observed image are discriminated as: noisy and noise free pixels.

In the next stage, for the suppression of RVIN effectively one weighted window of size 3×3 is taken, where $x_{i,j}$ is the central pixel in the window.
With the help of a weighted median filter the noisy pixel is replaced with $r_{i,j}$ that can be expressed as,

$$r_{i,j} = median\left\{x\left(i-s, j-t\right) \mid \left(s,t\right) \epsilon W\right\} \tag{2.8}$$

where W is the weighted window The weighted median filter with weights,

$$\left\{h\left(s,t\right) \mid \left(s,t\right) \epsilon W \sum_{\left(s,t\right)\epsilon W} h\left(s,t\right) = c\right\} \tag{2.9}$$

where c is an odd integer greater than or equal to the window size. This process is repeated until the weighted window is processed for the entire noisy image.

2.3 Results and Discussions

The proposed noise suppression algorithm is tested with various standard gray level images including *Cameraman, Lena, Barbara, Goldhill, Monarch, bird* etc. of size 256×256, corrupted by random valued impulse noise of various densities. The performance comparison is made with some standard methods like ACWM, PWMAD and DWM. The performance of the noise suppression filter which is used in the proposed method is measured by the parameter peak signal-to-noise ratio. In addition, the computational cost is evaluated using running time (RT) with a 2.6GHz CPU.

Figures (2.1), (2.2) and (2.3) show the reconstructed images for the *Lena, Cameraman and Barbara* degraded with various densities of random valued impulse noise respectively. The performance comparisons of the same images for various densities of noise levels are shown in Table (2.1), (2.2) and (2.3). It is observed that in these experiments, the proposed method provides relatively satisfactory results in effective noise suppression with preserving detailed informations as compared to the ACWM, PWMAD and DWM methods.

2.4 Summary

This chapter proposes a new scheme for the suppression of random valued impulse noise from images. By using the Bayesian classifier the pixels of the test image can be detected as noisy or not. Then the noisy pixel is replaced by a weighted median filter. Implementation of this scheme and comparison of results with previous scheme has been made thoroughly. It is verified that due to its simplicity this algorithm requires very low computational cost.

(a) (b) (c) (d) (e) (f)

Figure 2.1: (a) Original *Lena* image, (b) Noisy image with 20% of random valued impulse noise, (c) Restored image with ACWM [16], (d) Restored image with PWMAD [17], (e) Restored image with DWM [18], (f) Restored image with proposed method.

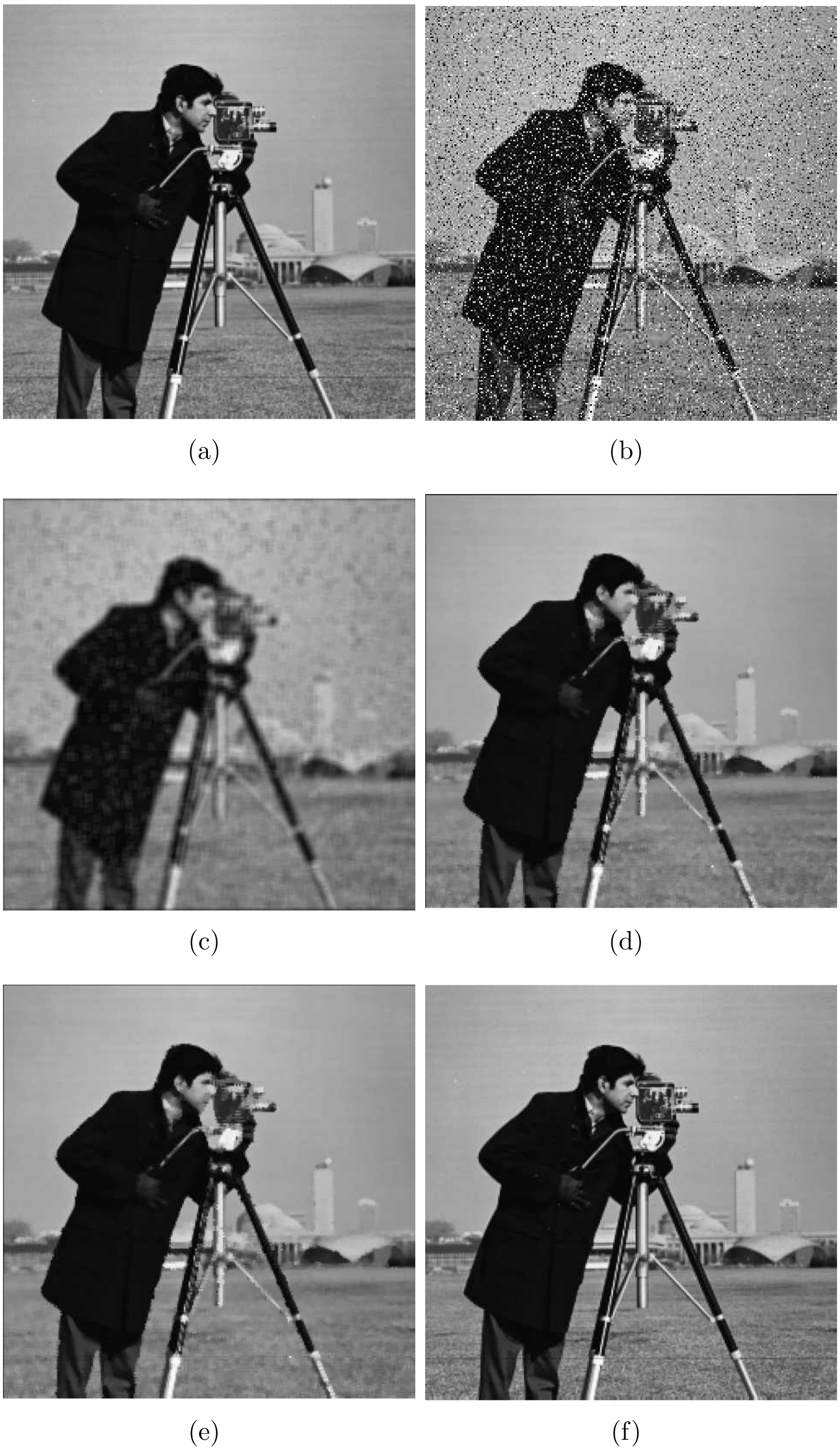


Figure 2.2: (a) Original *Cameraman* image, (b) Noisy image with 20% of random valued impulse noise, (c) Restored mage with ACWM [16], (d) Restored image with PWMAD [17], (e) Restored image with DWM [18], (f) Restored image with proposed method.

(a) (b)

(c) (d)

(e) (f)

Figure 2.3: (a) Original *Barbara* image, (b) Noisy image with 20% of random valued impulse noise, (c) Restored image with ACWM [16], (d) Restored image with PWMAD [17], (e) Restored image with DWM [18], (f) Restored image with proposed method.

Table 2.1: Performance Comparisons of *Lena* Image

Noise	Methods	PSNR	RT(msec)
5%	ACWM [16]	35.72	78.5
	PWMAD [17]	36.46	55.1
	DWM [18]	36.05	12.4
	Proposed	37.12	10.2
10%	ACWM	34.47	78.8
	PWMAD	34.86	55.8
	DWM	35.15	12.6
	Proposed	36.01	10.2
15%	ACWM	33.41	79.2
	PWMAD	32.69	57.5
	DWM	34.48	13.2
	Proposed	35.12	10.9
20%	ACWM	32.44	81.6
	PWMAD	30.58	57.9
	DWM	33.81	13.7
	Proposed	34.75	11.1
25%	ACWM	31.35	82.3
	PWMAD	28.01	58.4
	DWM	33.09	14.1
	Proposed	33.97	11.7
30%	ACWM	30.40	82.8
	PWMAD	25.94	59.2
	DWM	32.43	14.8
	Proposed	33.01	12.3
40%	ACWM	27.86	83.3
	PWMAD	22.41	60.1
	DWM	30.64	15.1
	Proposed	32.11	12.6
50%	ACWM	25.66	84.2
	PWMAD	19.42	60.8
	DWM	29.14	15.8
	Proposed	30.37	13.1

Table 2.2: Performance Comparisons of *Cameraman* Image

Noise	Methods	PSNR	RT(msec)
5%	ACWM [16]	33.43	76.2
	PWMAD [17]	34.13	54.7
	DWM [18]	35.28	11.5
	Proposed	36.98	8.9
10%	ACWM	32.79	76.8
	PWMAD	33.26	54.9
	DWM	34.96	11.8
	Proposed	35.85	9.3
15%	ACWM	32.09	78.3
	PWMAD	33.42	55.4
	DWM	34.07	12.1
	Proposed	35.02	9.7
20%	ACWM	31.84	79.6
	PWMAD	32.88	55.9
	DWM	33.81	12.8
	Proposed	34.65	10.1
25%	ACWM	30.46	80.7
	PWMAD	31.41	57.2
	DWM	33.01	12.2
	Proposed	34.08	10.1
30%	ACWM	29.85	81.3
	PWMAD	30.32	58.4
	DWM	31.97	12.8
	Proposed	32.82	10.5
40%	ACWM	28.91	82.5
	PWMAD	29.62	58.9
	DWM	30.08	14.2
	Proposed	31.51	11.2
50%	ACWM	27.04	83.2
	PWMAD	28.03	59.8
	DWM	29.19	14.9
	Proposed	29.77	12.4

Table 2.3: Performance Comparisons of *Barbara* Image

Noise	Methods	PSNR	RT(msec)
5%	ACWM [16]	32.25	75.7
	PWMAD [17]	33.36	54.4
	DWM [18]	34.09	11.9
	Proposed	35.52	8.8
10%	ACWM	31.78	76.1
	PWMAD	32.06	55.1
	DWM	33.55	11.1
	Proposed	34.31	8.8
15%	ACWM	30.61	77.3
	PWMAD	31.04	55.7
	DWM	32.48	11.7
	Proposed	33.93	9.2
20%	ACWM	29.97	78.1
	PWMAD	30.58	56.3
	DWM	31.71	12.2
	Proposed	32.85	9.5
25%	ACWM	28.65	78.8
	PWMAD	29.81	57.2
	DWM	30.67	12.6
	Proposed	31.43	9.5
30%	ACWM	28.04	80.5
	PWMAD	28 .99	57.7
	DWM	29.52	13.1
	Proposed	30.86	10.1
40%	ACWM	27.77	81.4
	PWMAD	28.81	58.3
	DWM	29.24	13.8
	Proposed	30.21	10.8
50%	ACWM	26.69	82.7
	PWMAD	27.16	58.9
	DWM	28.79	14.5
	Proposed	29.12	11.3

Chapter 3

Improved SADA to Suppress Gaussian Noise

Chapter 3

Improved Spatially Adaptive Filtering to Suppress Gaussian Noise

Spatially adaptive denoising algorithm (SADA) provides satisfactory results when the image is corrupted with the SNR level $\geq$ 10 dB of additive white Gaussian noise. But when the image is corrupted seriously with SNR level less than 10dB, then the SADA does not lead to satisfactory results. This chapter proposes an improved version of SADA which gives satisfactory results in terms of objective and subjective when the image is corrupted with the SNR level, less than 10dB of Gaussian noise. Generally, suppression of Gaussian noise poses a trade off problem between denoising and preserving the detailed information of the image. So in the proposed method, the parameters of local statistics are used for effective noise suppression with preserving detailed informations as compared to PWMAD, SAWM and SADA methods. Noise detection and noise suppression are the two stages of the proposed method. By using the parameters of the local statistics, noise detection constraint is defined. Similarly by using a modified Gaussian filter based on the same local statistics parameters the detected noise of the image is suppressed. Error detection, computational cost, local statistics, over-smoothness and smoothing degree of reconstructed image are the parameters taken into account to suppress the Gaussian noise components in the proposed method.

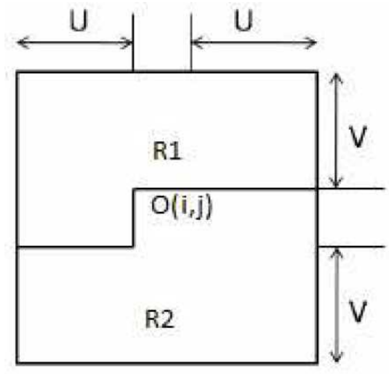


Figure 3.1: Local window

3.1 Proposed Method

In general, when an original image is degraded by additive Gaussian noise which is signal independent, then the usual degradation model at a point (i, j) can be represented as,

$$O(i, j) = I(i, j) + n(i, j) \tag{3.1}$$

where I represents the original image, O represents the observed noisy image and n represents the additive noise which is signal independent respectively.

For the noise suppression, a window based concept is used in which a local window of size $(2U + 1) \times (2V + 1)$ is considered as shown in Figure 3.1, where $U = 1$ and $V = 1$. The local window is divided into two regions $R1$ and $R2$, where $R1$ signifies the dark region and $R2$ signifies the white region. The intersection between $R1$ and $R2$ is null. The dark region consists of the filtered pixels and the the white region consists of the observed pixels. The noise detection constraints are defined with the help of the local statistics parameters such as the local weighted mean ($\mu_{i,j}$), the local weighted variance ($\sigma_{i,j}$) and the local maxima ($O_{max}(i, j)$) because these parameters are effectively used to control the degree of noise suppression. In the observed portion of the local window, these constraints are computed for a pixel O(i,j) with the help of the equations (3.2), (3.3) and (3.4).

$$\mu_{i,j} = \frac{\sum_k \sum_{l,(k,l)\epsilon R1} w(k, l)\hat{x}(i + k, j + l) + \sum_k \sum_{l,(k,l)\epsilon R2} w(k, l)O(i + k, j + l)}{\sum_k \sum_{l,(k,l)\epsilon R1} w(k, l) + \sum_k \sum_{l,(k,l)\epsilon R2} w(k, l)} \tag{3.2}$$

$$\sigma_{i,j} = \frac{\sum_k \sum_{l,(k,l)\epsilon R1} w(k,l)|\hat{x}(i+k,j+l) - \mu_{i,j}| + \sum_k \sum_{l,(k,l)\epsilon R2} w(k,l)x}{\sum_k \sum_{l,(k,l)\epsilon R1} w(k,l) + \sum_k \sum_{l,(k,l)\epsilon R2} w(k,l)} \tag{3.3}$$

where $x = |O(i+k, j+l) - \mu_{i,j}|$

$$O_{max}(i,j) = max(max_{(k,l)\epsilon R1}\hat{x}(k,l), max_{(k,l)\epsilon R2}O\,(k,l)) \tag{3.4}$$

where, $w(k,l)$ is the weighting coefficient at the point (k,l), within the window. These local statistical parameters are utilized to detect the noisy pixel by constructing a flag defined as,

$$flag(i,j) = \begin{cases} 1, & \text{if } O(i,j) > (\mu_{i,j} + F_{i,j}) \text{ or } \text{ if } O(i,j) < (\mu_{i,j} - F_{i,j}) \\ 0, & \text{otherwise} \end{cases} \tag{3.5}$$

where,

$$F_{i,j} = m \times \frac{\sigma_{i,j}}{O_{max}(i,j)} \tag{3.6}$$

and m is a constant value.

This shows the effects of local statistics for the noise detection. As smaller $F_{i,j}$ represents tighter bounds, so the additive noise can be easily detected in the flat region and a higher activity region tends to the looser bounds. This is the agreement of the masking property of noise [24]. With the help of the parameters of local statistics, the pixel of the observed portion of the local window can be detected as noisy or not.

In the next step, using the Gaussian filter, the noisy pixel is reconstructed. As the Gaussian filter is defined as a function of local statistics, which is very useful to control the degree of the smoothness of the reconstructed image, so it is an adequate way for using it for the suppression of noise. The Gaussian filter is defined as,

$$h_{i,j} = \frac{1}{S} exp\left\{-P\frac{\sigma_{i,j}^2(i^2+j^2)}{\sqrt{\mu_{i,j}+1}}\right\} \tag{3.7}$$

where S represents the normalizing constant and P represents a tuning parameter. The parameter P controls smoothness degree of the reconstructed image. The smaller P leads to stronger low-pass filtering which results over-smoothness around edge information whereas larger P leads to weaker low-pass filtering but suppression of noise is not satisfactory. The reconstructed pixel for the noisy pixel is defined as,

$$\hat{x}_{i,j} = \frac{\sum_k \sum_{l,(k,l)\epsilon R1} h(k,l)\hat{x}(i+k,j+l) + \sum_k \sum_{l,(k,l)\epsilon R2} h(k,l)O(i+k,j+l)}{\sum_k \sum_{l,(k,l)\epsilon R1} h(k,l) + \sum_k \sum_{l,(k,l)\epsilon R2} h(k,l)} \tag{3.8}$$

This process is repeated until the local window is processed for the entire input image.

3.2 Results and Discussions

The proposed noise suppression algorithm is tested with various standard gray level images including *Cameraman, Lena, Goldhill, Monarch, bird* etc. of size 256×256, corrupted by Gaussian noise of various levels of SNR. The performance comparison is made with some standard methods like PWMAD, SAWM and SADA. The performance of the noise suppression filter which is used in the proposed method is measured by the parameter peak signal-to-noise ratio. In addition, the computational cost is evaluated using running time (RT) with a $2.6GHz$ CPU.

In this work, the weighting coefficients are of uniform value i.e. 3 is used for computing the weighted mean value to reduce the computational cost by avoiding a division operation. By taking this uniform value over-smoothness can be avoided. As m in the flag is higher, the bounds are looser, which leads to higher missing detection error. Otherwise, tighter bounds shows higher fault detection error. It is observed that $0.01 \leq m \leq 0.1$ is a good range to use to minimize the error detection as per SADA. The tuning parameter P in the modified Gaussian filter represents the smoothing degree of the reconstructed image. If P is smaller then, stronger low-pass filtering is applied to suppress the additive noise. However, smaller P shows over-smoothness around edge information. Otherwise, larger P results in weaker low-pass filtering. On the basis of these experiments, it is verified that $0.01 \leq m \leq 0.07$ is the perfect range for taking the value of m. In this work, $m = 0.05$ is used.

Figure 3.2: (a) Original *Lena* image, (b) Noisy image with 5 dB of Gaussian noise, (c) Restored image with PWMAD [17], (d) Restored image with SAWM [14], (e) Restored image with SADA [15], (f) Restored image with proposed method.

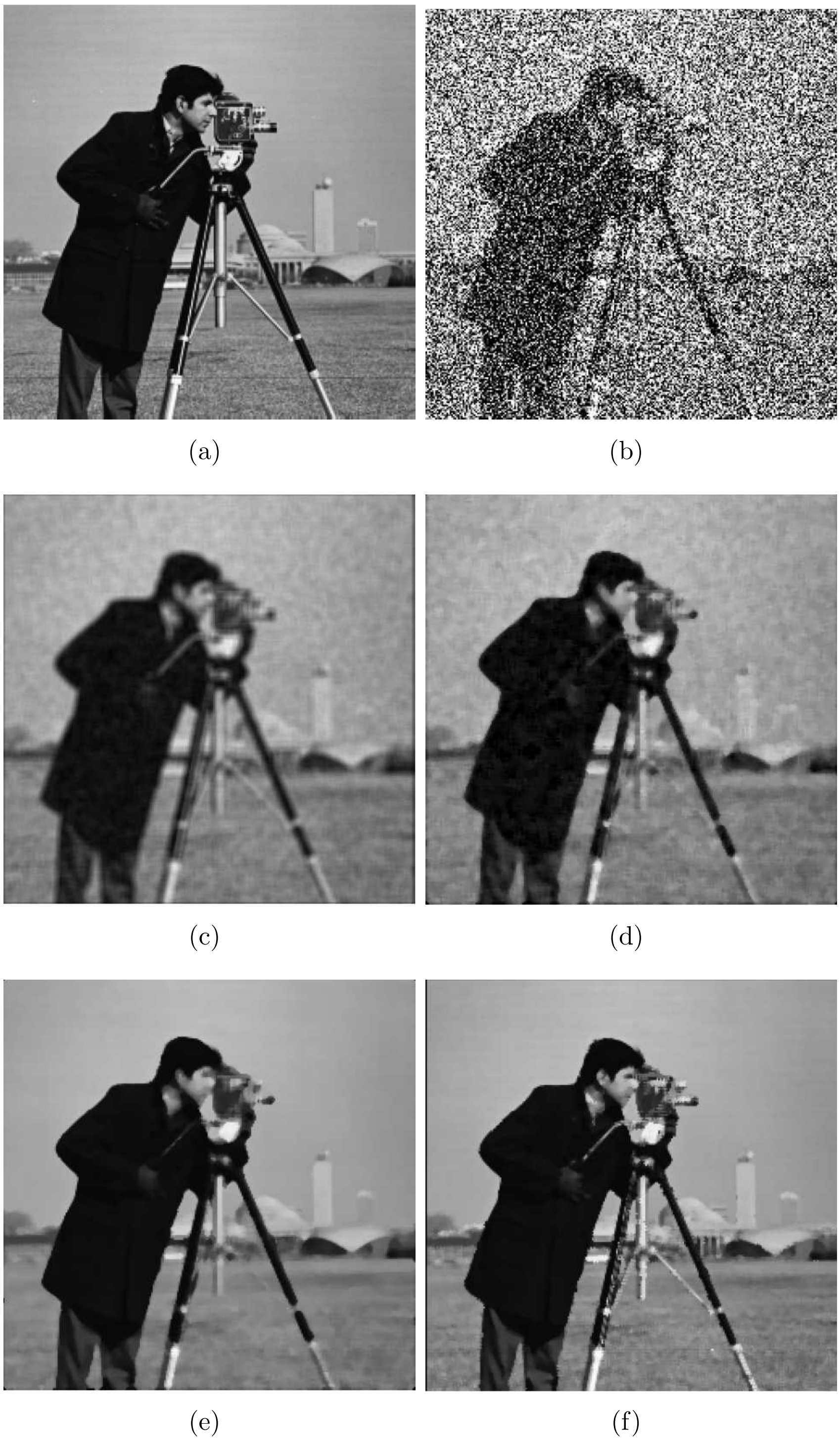
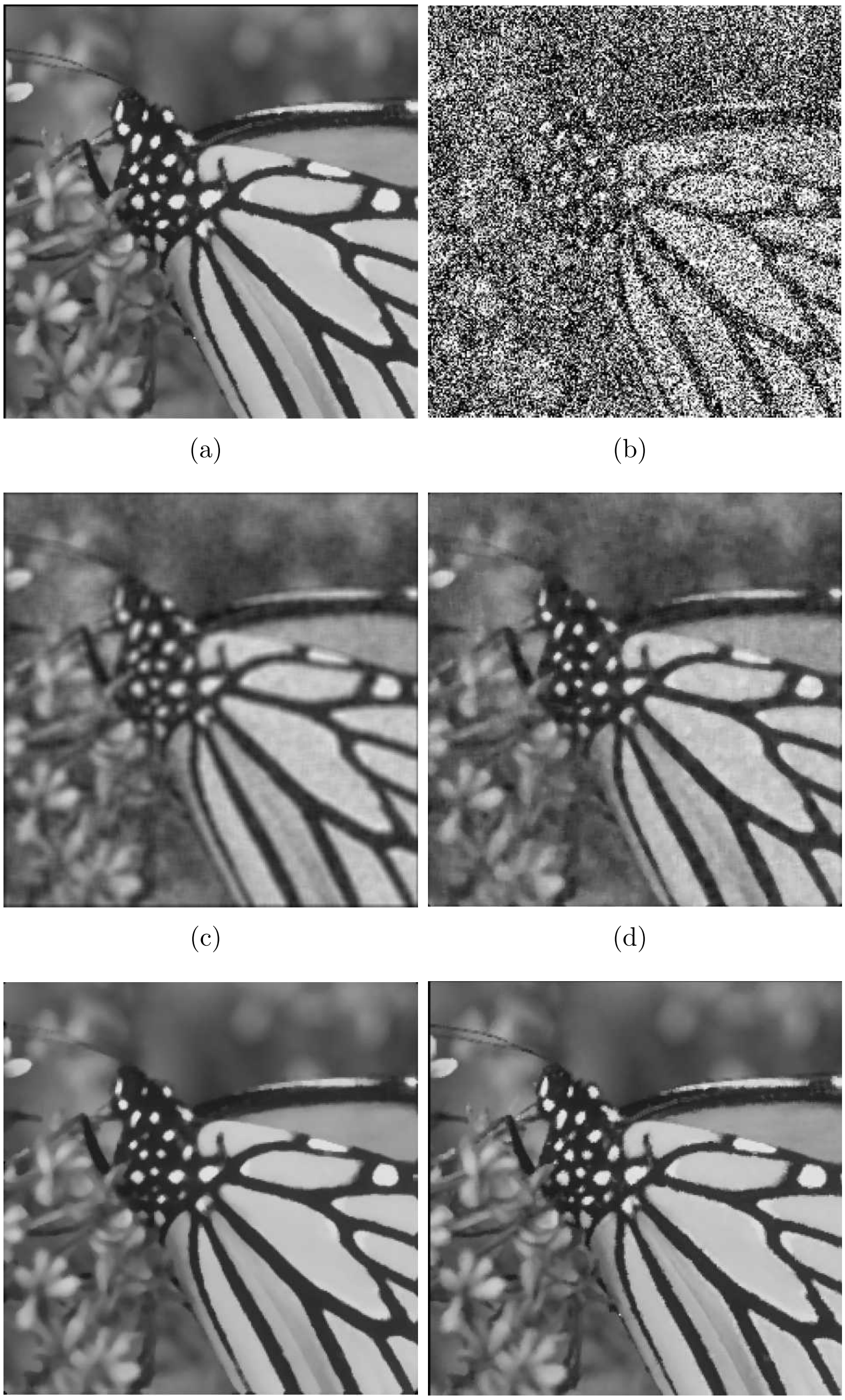


Figure 3.3: (a) Original *Cameraman image*, (b) Noisy image with 5 dB of Gaussian noise, (c) Restored image with PWMAD [17], (d) Restored image with SAWM [14], (e) Restored image with SADA [15], (f) Restored image with proposed method.



(a) (b) (c) (d) (e) (f)

Figure 3.4: (a) Original *Monarch image*, (b) Noisy image with 5 dB of Gaussian noise, (c) Restored image with PWMAD [17], (d) Restored image with SAWM [14], (e) Restored image with SADA [15], (f) Restored image with proposed method.

Figures (3.2), (3.3) and (3.4) show the reconstructed images for the *Lena, Cameraman and Monarch* image degraded with 5 dB of Gaussian noise respectively. The performance comparisons of the same images for various SNR levels are shown in Table (3.1), (3.2) and (3.3). It is observed that in these experiments, when the noise level is relatively high, i.e. less than 10dB, then PWMAD, SAWM and SADA leads to overly blurred results whereas the proposed method provides relatively satisfactory results in effective noise suppression with preserving detailed informations. But when the noise level is low i.e. $\geq$ 10 dB, then the proposed method gives similar results as SADA.

Table 3.1: Performance Comparisons of *Lena* Image

Noise	Methods	PSNR	RT(msec)
3(dB)	PWMAD [17]	24.02	185.9
	SAWM [14]	24.88	124.7
	SADA [15]	26.31	8.7
	Proposed	27.95	8.6
5(dB)	PWMAD	25.05	185.2
	SAWM	25.73	123.1
	SADA	27.01	8.7
	Proposed	28.52	8.6
10(dB)	PWMAD	27.77	184.9
	SAWM	27.84	121.5
	SADA	29.45	8.6
	Proposed	29.45	8.6
20(dB)	PWMAD	30.64	182.2
	SAWM	30.95	118.9
	SADA	32.36	8.8
	Proposed	32.36	8.8
30(dB)	PWMAD	31.24	180.5
	SAWM	31.90	117.1
	SADA	33.09	8.7
	Proposed	33.09	8.7

Table 3.2: Performance Comparisons of *Cameraman* Image

Noise	Methods	PSNR	RT(msec)
3(dB)	PWMAD [17]	22.82	188.2
	SAWM [14]	23.01	123.1
	SADA [15]	25.01	8.6
	Proposed	26.75	8.5
5(dB)	PWMAD	23.03	187.1
	SAWM	23.83	121.7
	SADA	26.21	8.6
	Proposed	27.35	8.5
10(dB)	PWMAD	25.08	183.4
	SAWM	25.93	120.3
	SADA	28.11	8.7
	Proposed	28.11	8.7
20(dB)	PWMAD	27.06	183.1
	SAWM	27.38	119.7
	SADA	29.77	8.6
	Proposed	29.77	8.6
30(dB)	PWMAD	27.32	178.9
	SAWM	27.70	115.6
	SADA	30.31	8.7
	Proposed	30.31	8.7

3.3 Summary

A novel method has been proposed to suppress the Gaussian noise when the image is highly corrupted with the SNR level of less than 10dB of Gaussian noise. Noise detection and noise suppression filter are defined using the parameters of local statistics. As the local activity is effectively used to control the degree of noise suppression, so the proposed method leads to relatively satisfactory results in effective noise suppression with preserving detailed informations whereas PWMAD, SAWM and SADA leads to overly blurred results. Also it is observed that the degree of over smoothness is more visible with the other approaches. In the proposed method, the uniform weighting coefficients and all pixels including the diagonal pixels within the local window are the important parameters used to calculate the local information as well as to obtain a better filtering performance.

Table 3.3: Performance Comparisons of *Monarch* Image

Noise	Methods	PSNR	RT(msec)
3(dB)	PWMAD [17]	30.05	188.8
	SAWM [14]	31.02	124.5
	SADA [15]	32.91	8.7
	Proposed	33.89	8.6
5(dB)	PWMAD	30.93	187.5
	SAWM	31.85	123.8
	SADA	33.78	8.7
	Proposed	34.12	8.6
10(dB)	PWMAD	32.25	185.8
	SAWM	33.17	121.5
	SADA	34.23	8.6
	Proposed	34.23	8.6
20(dB)	PWMAD	34.19	182.2
	SAWM	35.95	118.9
	SADA	37.36	8.8
	Proposed	37.36	8.8
30(dB)	PWMAD	38.24	180.5
	SAWM	39.90	117.1
	SADA	40.35	8.8
	Proposed	40.35	8.8

Chapter 4

Conclusion and Future Work

Chapter 4

Conclusion and Future Work

Image noise is a common phenomenon that exists in many applications like photography, communications etc. Number of methods have been devised to suppress the noise from image. However, the problem is still open and requires significant research. In this thesis attempts have been made to suppress random valued impulse noise and Gaussian noise from images. Two contributions are made in this regard. Chapter two deals with removing RVIN from images by detecting the pixels as noisy or noise free. The noisy pixels detection is modeled as pattern classification problem. The well known Bayesian classifier has been utilized to classify a pixel as noisy or non noisy. Later, the noisy pixels are filtered out using weighted median filters, while keeping noise free pixels intact. Chapter three deals with improving the existing SADA approach for Gaussian noise suppression. However, the proposed scheme works better than SADA for the image corrupted with high level Gaussian noise and gives same results with low noise conditions. Exhaustive simulations are carried out on standard images for both the proposition and performance comparison is made with other state of the art techniques. It has been observed that the proposed schemes provides better results than the existing schemes both in terms of noise rejection and retention of original image properties.

Scope for Further Research

The research findings made out of this thesis has opened several research directions, which gives scopes for further investigation. The proposed schemes can be extended to deal with color images. A better classifier can be designed or comparision between several classifiers can be done for detecting a noisy pixel. It is also assumed that most of the denoising problems can be modeled as multi objective optimization problem for better image quality.

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Dissemination

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   International Journal of Computer Applications (0975-8887), Vol. 67, no. 17, pp 5–8, April 2013, India.